[1]*Reena Kumari
[2] Neha Rani
[3]Rashmi Rani
[4]Chandan Kumar
[5]Jyoti
[6]Vijeta Bachan

Future Prospects and Recent Advancements in Machine Learning for Assessing the Service Life and Durability of Reinforced Concrete Buildings

Journal of Electrical Systems

***Abstract:* -** For necessary action to be taken in a timely and economical way, accurate service-life forecast of buildings is essential. But the oversimplified assumptions of the traditional prediction models result in approximations that are not correct. The capacity of "machine learning" to overcome the shortcomings of traditional future models is reviewed in this research. This can be attributed to its capacity to represent the intricate physical and chemical dynamics of the degradation mechanism. The study also summarizes other studies that suggested "machine learning" may be used to support the assessment of reinforced concrete building durability. Comprehensive discussion is also held regarding the benefits of using machine learning to evaluate the service life and durability of "reinforced concrete" buildings. It is becoming easier to apply "machine learning for durability and service-life" evaluation thanks to the growing trend of wireless sensors gathering an increasing amount of in-service data. In light of the most recent developments and the state of the art in this particular field, the presentation ends by suggesting future directions.

Keywords: Machine learning, concrete, durability, degradation, Service life.

I. INTRODUCTION

One of the biggest issues the construction industry has encountered over the past few decades is the longevity and "service life of reinforced concrete" structures. Worldwide, corrosion-induced degradation of reinforced concrete structures is a serious concern [1–8]. Rebuilding and maintaining RC structures due to corrosion has reportedly been estimated to cost billions of dollars annually. Every year, Western Europe alone must spend 5 billion EUR on repairing damage caused by rust [9]. Remarkably, several wealthy nations allocate around 3.5% of their GDP [10] on mitigating damage caused by corrosion and controlling associated issues.

Alternatively, 37% of failure modes in reconstructed reinforced concrete buildings are caused by ongoing corrosion of the reinforcing bar, or rebar [11–13]. This is the general type of degradation in these types of reconstructions. As a result, making repairs becomes expensive and time-consuming.

To estimate a structure's stability and service life, a clear understanding of the concrete's performance is essential. A single degradation mechanism is often used to evaluate the performance of concrete. The performance of concrete is really impacted by a number of intricate degrading processes that may occur concurrently or subsequently [14, 15]. When many actions contribute to the deterioration process, the combined effect of the synergistic degradation processes is more rapid and severe [16–18]. It is not practical to measure the combined degrading processes' influence in a lab and then translate the results to a real building. Additionally, doing concrete performance investigations in the field or in a lab can sometimes take a lot of time and money, both directly and indirectly [19]. For e.g., traditional highway structure in-service scrutiny and prevention programmes result in traffic delays, which can account for 15% to 40% of the construction expenses [20]. Therefore, life-cycle management of reinforced concrete buildings requires an accurate and affordable assessment of the concrete's performance throughout operation from both an economic and safety standpoint.

Installing durability monitoring systems in reinforced concrete structures may make it possible to spot degradation early on. One essential prerequisite for improving the stability evaluation of reinforced concrete frames is the availability of short- and long-term data from the monitoring system with temporal and geographical resolution. To determine how long a structure will likely be in service, data gathered from the monitoring system must be effectively analyzed. In fact, without the ability to draw conclusions or knowledge from them, statistics are meaningless on their own [21,22].

The circumstances leading to rebar corrosion in reinforced concrete buildings are discussed in Section 2. The same part also discusses the limitations of the typical models that are used to assess the resilience and balance service life of RC

[1] *Reena Kumari: Department of CSE, Bakhtiyarpur College of engineering, Bihar, India
Email: reenanerist@gmail.com
[2] Neha Rani: Department of CE, Government engineering college Bhojpur, India
[3] Rashmi Rani: Department of EE, Government engineering college Nawada, India
[4]Chandan Kumar: Department of CE, Government engineering college Bhojpur, India
[5]Jyoti: Department of CE, Government engineering college Bhojpur, India
[6]Vijeta Bachan: Department of CE, Government engineering college Buxar, India

(reinforced concrete) structures. Part 3 provides the essential information about machine learning. Two specific domains in field of civil engineering are the subject of discussion on the utilization of "ML" strategy in Section 4. Section 5 outlines the current applications of "machine learning" approaches in service-life and durability evaluation, along with durability monitoring systems. In the same part, the future orientation of the service-life forecast technique and durability monitoring is also outlined. In Section 6, a final conclusion is provided.

2 Durability and service life of RC structures-

The most common causes of rebar corrosion in concrete are either carbon dioxide (CO2) or chloride ions (Cl^-) seeping into the pores of the material. Because of its naturally alkaline pore solution pH of 12–13, embedded rebar is passivise. The carbonation of concrete or the existence of Cl^- both weaken the passivation of rebar [23–25]. A physicochemical process known as carbonation is brought about spontaneously when CO2 from the surrounding air seeps into the pores of concrete and interacts with the hydrated cement [26, 27]. Rebar may corrode due to both carbonation and chloride, which may minimize its cross-sectional area, elongation ability, and generate significant cracks in the concrete. All of these factors can significantly lower the structure's ability to support weight. An increased rate of rebar corrosion and concrete deterioration might result from cracked concrete providing easier access to moisture and hostile gases and ions such oxygen (O2), carbon dioxide (CO2), and chlorine (Cl). Concrete constructions will thus have reduced strength, durability, serviceability, and safety [6–8, 28]. Rebar corrosion brought on by carbon action can affect a larger area of reinforced concrete buildings more extensively and more expensively to repair than corrosion brought on by chloride. Around two thirds of all concrete buildings are thought to be subjected to climatic conditions that encourage corrosion caused by carbonation [29, 30]. beginning and propagation are the two stages of the corrosion-generate degradation of RC "reinforced concrete" structures. While the rebar is still passivated, the diffusion of CO2 gas into the concrete marks the beginning of corrosion in the event of carbonation-induced corrosion. When it comes to corrosion caused by chloride, the process of Cl^- entering concrete is equivalent to the corrosion beginning phase. Starting from the point at which rebar corrosion begins and ending with structural failure is known as the propagation period. Comparing this phase to the stage of corrosion beginning, it is rather brief. These reasons have led to the routine use of the first stage's duration to determine the RC structures' longevity and service life [31, 32] As seen in Fig. 1.

2.1 **Deterioration models**

In order to effectively estimate concrete performance and make decisions about the maintenance and rehabilitation of reinforced concrete buildings, degradation models are essential. Significant efforts have been undertaken over the last thirty years to create durability models for reinforced concrete buildings subjected to environmental factors that encourage corrosion caused by carbonation and chloride. As a result, many prototypes and input data has been developed [33-36]. A number of the applied analytical models and the associated input parameter values have been found to be inaccurate, lacking, or inappropriate for the current circumstances. Because of these factors, even for the same concrete matrix exposed under the same circumstances, the forecast results varied significantly [37]. Although complex scientific models can yield relatively accurate predictions, they are not user-friendly and need highly experienced professionals, making them unsuitable for practical design applications. In real-world applications, CO2 and Cl^- penetration into concrete is often modelled using empirical degradation models, which take the form of straightforward analytical equations based on Fick's second law of diffusion.

2.1.1 Carbonation model-

One of the main factors causing RC constructions' early degradation, loss of serviceability, and safety concerns has been identified as concrete carbonation. It is a crucial indicator of longevity. According to Fick's second rule of diffusion, the traditional "carbonation depth forecast model" is represented in Eq. (1) [26,38–41]. By extending the carbonation depth recorded at one point in time to the future, this model—which is square root law compliant—may be used to predict the depassivation time.

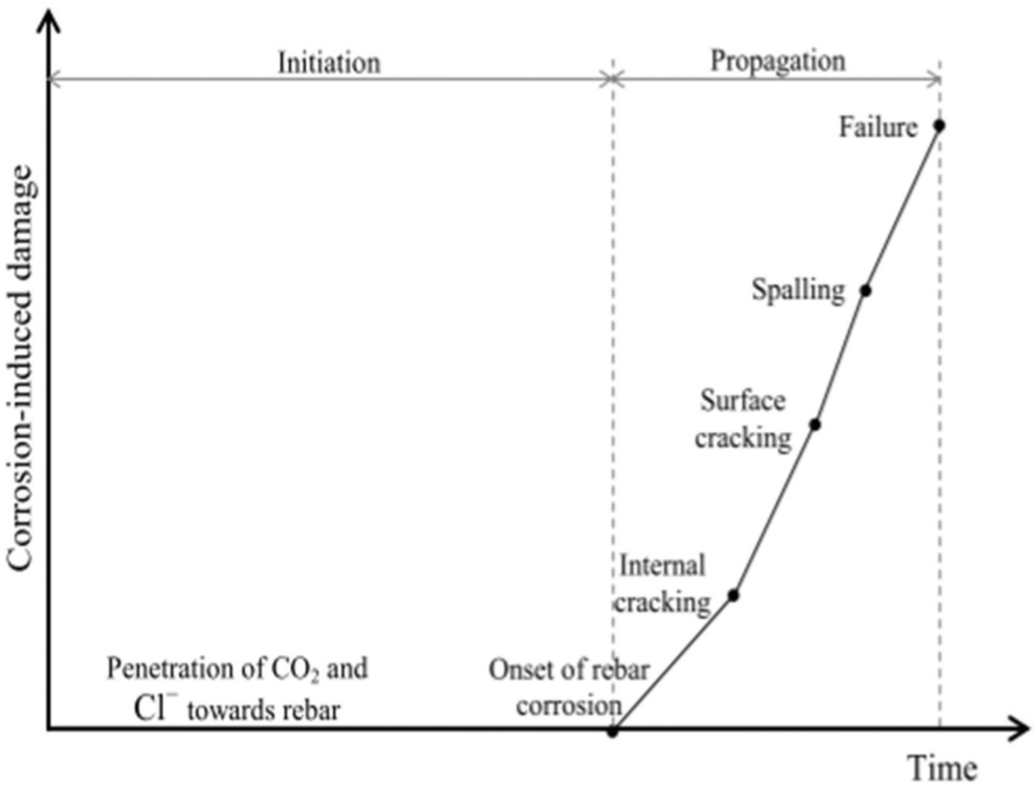

Fig. 1. Schematic depiction of the method of rebar corrosion

2.1.2.1.1 Chloride model-

Because chloride attack has an impact on the "remaining service life of RC structures", predicting the chloride profile is a needed step. Several methods have been developed throughout the years to forecast the focus of chloride within concrete. Despite the availability of a variety of methods, empirical models are most typically used to approximate the chloride detail in concrete. this is an empirical calculation depends on "Fick's second law", which is used to assess "long-term chloride penetration" in concrete.

2.2 **Modelling uncertainty-** The starting period of "carbonation-induced corrosion" is the amount of time it takes for the carbonation front to reach a depth in the concrete cover. If the carbonation coefficient k and the thickness of the concrete cover are known, the start time may be determined with a simplified Fick's law-based calculation, Eq. (1). Eq. (1) makes the following assumptions: (i) the diffusion coefficient of CO2 through carbonated concrete is constant; (ii) the amount of CO2 required to neutralize alkalinity within a unit volume of concrete is constant; and (iii) CO2 concentration varies linearly between fixed boundary values of C1 at the external surface and C2 at the carbonation front. To calculate k, the concrete carbonation depth must be measured beforehand, either by measuring the carbonation depth of an existing structure or by conducting an accelerated test. Because carbonation is a slow process, it is often investigated using an accelerated test with greater CO2 concentrations in a controlled setting [43]. Using the observed carbonation depth, the equivalent k and hence the time of rebar depassivation may be calculated. This technique is often used, albeit the accelerated test may not always accurately describe the natural carbonation process [39]. Eq. (1) is feasible as long as all three assumptions are met, however the CO2 diffusion coefficient changes both temporally and geographically. These variations are due to the fact that CO2 diffusion is influenced by a variety of factors, including CO2 concentration, concrete composition, curing, and ambient variables [38,43,44]. As a result, Eq. (1) frequently fails to describe the actual condition of concrete buildings, resulting in inaccurate carbonation depth prediction [26,44,45]. To reduce some of the assumptions, empirical models have been proposed that take into direct account the influence of some factors that govern the rate of carbonation, such as the fib-MC2010 [46] and DuraCrete framework [47]. The fib and DuraCrete models adopt Eq. (1) by linking the coefficient of carbonation with concrete material and environmental factors. There are more models that follow the same logic. The related characteristics have traditionally been viewed as frequent variables that determine the qualities of concrete that control CO2 infiltration rate, just like exposure, "water-to-binder ratio" (w/b), and "compressive strength". The permeability of concrete controls many of the physical-chemical processes associated with CO2 passage through it. Although the penetrable coefficient of concrete is primarily determined by the w/b ratio, additional elements such as aggregate distribution, age, curing conditions, and the presence of chemical or mineral admixtures also have an impact. The bulk of the improved models do not incorporate all of the regulating data that effect the process. Integrating of these prototypes not fix the issue. The mixing of so many simplifications and assumptions in current carbonation expectation models results in significant uncertainty in their performance. The bulk of the enhanced prototypes do not incorporate all of the regulating data that influence the carbonation activity. Integrating two or more of these prototypes does not fix the issue. The joining of many conspectus and supposition in current carbonation forecasting models results in significant uncertainty in their functioning [28, 48-50]. In another viewpoint, cement type, w/b, age, admixture type, and exposure situation all influence the transformation of concrete's capillary pore structure. As a result, both Cs and Dnss fluctuate throughout space & time [51, 52]. This demonstrates that Dnss is a operation of Cs, therefore the assumption (iii) used is erroneous. Furthermore, the error function equation in only takes into account the diffusion process [50]. Indeed, various ways have been developed to handle the temporal dependency of DNS and the influence of other significant variables, such as fib-MC2010 [46] and the DuraCrete framework [47]. The most popular one is represented in equation [49,53]. This uncertainty might have serious consequences in terms of poor design, inspection, and maintenance planning, reducing the structure's service life and increasing lifecycle costs. The rate of CO2 and Cl− penetration into concrete depends on its qualities and environmental circumstances, as previously described. In real structures, the entrance rate of these chemicals cannot be constant, and it may even vary across various regions of a single constituent. As a result, “carbonation and chloride attack” depassivates the rebar in a highly complicated manner. In reality, basic empirical degradation models may be combined with a semi-probabilistic uncertainty model to increase dependability, as is done in the “DuraCrete framework”. However, this strategy does not completely reduce the accompanying ambiguity.

3 **Machine learning**

“ML” is a prominent subject of “artificial intelligence” that deals with the generation and modification of algorithms for identifying complex shapes from observational data with no relying on a pre-established formula as a prototype and making intelligent judgements [54-62]. ML-oriented prototypes can be predictive or descriptive [58, 63, 64]. Even “ML” arose from the search for artificial intelligence, its reach and possibilities are far more widespread. It incorporates concepts from a variety of domains, involving as the theory of data, probability, statistics, brain science and psychology, control complex computation concept, and theology [61]. Developing a system for machine learning necessitates many design decisions. (i) an illustration of the objective variable; and (ii) a technique for learning the objective variable from examples used in training. Machine learning is divided into four categories depending on learning assets: controlled, “unsupervised”, semi-supervised, and “reinforcement learning” [58,65]. The two types of understanding are the most used machine learning algorithms in a wide range of sectors, notably engineering [64].

beginning with a learning data containing i/p occurrence and expected o/p, the aim of observed learning is to create a function that can accurately forecast the undefined goal o/p of subsequent examples. The availability of a "teacher" and learning i/p-o/p data is the most important feature of supervised learning. Regression is a task that involves predicting continuous target variables. However, categorization refers to the problem of predicting discrete target variables. Unsupervised learning: beginning with a learning data that contains input instances, the purpose is to partition the training examples into clusters with high levels of closeness. Unsupervised learning, unlike supervised learning, does not have data labels accessible.

To address issues using machine learning approaches, an algorithm must be created. Machine learning algorithms use approaches from a variety of domains, such as design recognition, data mining, statistics, and “signal processing”. It permits ML to benefit from the synergy of all these professions, resulting in solid solutions that employ several regions of knowledge [62]. Figure 2 depicts some of the most prominent tricks used in both unsupervised and supervised learning types. It is even worth noting that few algorithm types use distinct learning types to address different issues.

Today, machine learning has a broad range of effective practical applications in a variety of fields, including “computational finance” [66-68], picture and audio generation [69-71], quality estimation [72-74], “hydrology” [75-78], “computational biology” [79-82], and energy generation [83-85]. Even ML is being more famous in many technical disciplines, its use in assessing the stability and “service life of RC” remains restricted.

4 **Application of machine learning techniques in civil engineering**

Machine learning approaches have been widely used to simulate real-world issues during the last few decades due to their huge ability to capture interaction between data couple of i/p and o/p that are nonlinear, without known, or difficult to define. Even ML has limited utility in concrete service life evaluation, it has been used in other civil engineering challenges. Three decades ago, the earliest applications of ML strategy were evaluating several existing approaches on simple issues [86,87].

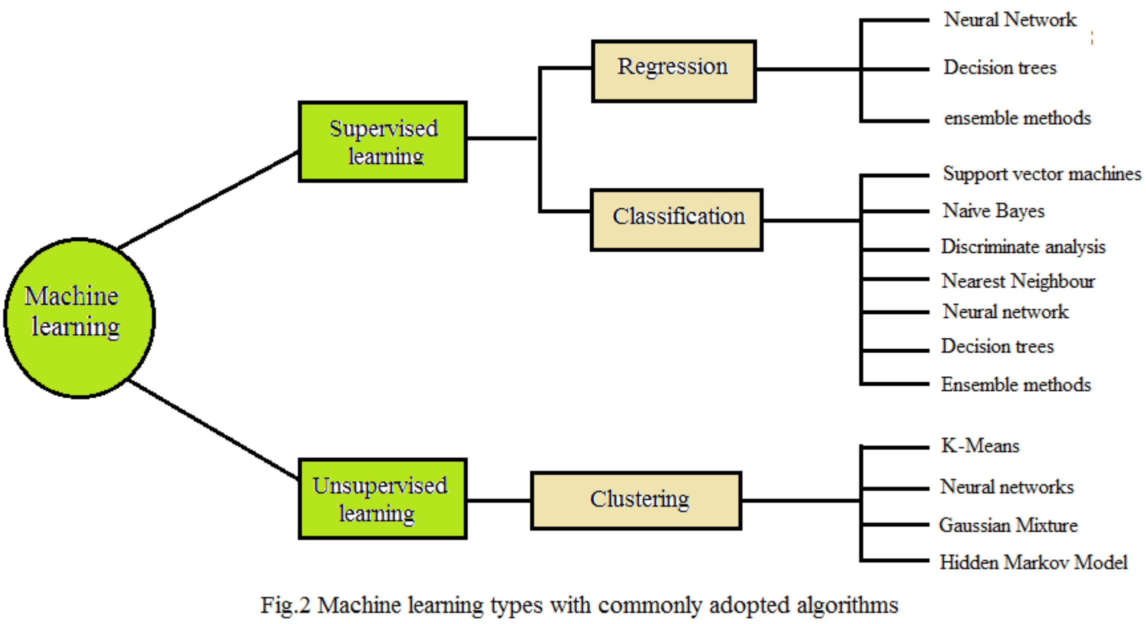

Fig. 2. Machine learning types with commonly adopted algorithms.

During that period, machine learning algorithms were chosen mostly based on their availability rather than their suitability to the target issue [59]. As a result, the appeal difficulty rendition was a simple influenced by the inadequacies of available machine learning techniques. Then, gradually, more difficult problems were considered. The most often used applications are structural health monitoring, concrete property evaluation, and mix design. In present portion, we see ML algorithms were implemented in these two applications.

4.1 Structural health monitoring

Structural degradation induced by environment and function is an unavoidable phenomenon in civil constructions. starting detection of structural degradation using a SHM system is critical for ensuring public service and dependability of in-"service structures" while preventing economic losses [88-91]. It entails observation a "structure over time" with dynamic outcome measurements spaced at constant intervals, extracting damage-sensitive characteristics, and statistically analyzing the derived features to find out the system's current health situation.

SHM systems are increasingly being implemented in a variety of structures, particularly long-length bridges, huge dams, and high buildings, allowing for a normal transition from "time-based to condition-based" prevention. So many studies have lately been conducted in this sector of intrigue, either using model-driven or data-driven methodologies [89,92]. A basic model-driven technique in SHM employs a mathematical prototype of the structure that links inconsistencies among observed data and prototype-produced value to detect a dam. This method is computationally demanding owing to repetitive examination of a computer simulation model [90]. Furthermore, in actuality, a numerical model may not always be available and does not always accurately reflect the specific performances of the actual structure [93].

Methods from machine learning are commonly used in supervised learning to identify structural damage when data from healthy and damaged conditions is necessary. Single machine learning techniques such as "neural network", "support vector machine", "support vector regression", and "genetic algorithm" are popular for structural harm recognition owing to their stability and success regardless of little data, ambiguity, and noise [89,94-96]. Hybrid methods to several SHM difficulties have been described, including the multiple goals genetic code, "neurofuzzy", and "wavelet neural network" [97-99]. Table 1 illustrates the suitability of several ML algorithms for measuring physical health and dam activity. The result analyses of every study indicated that "ML-based models" outperformed model-driven models.

4.2 Concrete characteristics and mix design

Elastic constants measurement is complex and "time-consuming" [111-114]. As a result, it is frequently derived from concrete's stress-strain relationships [115-117]. Due to the test's complexity, expense, and time-consuming nature, splitting tensile of concrete is frequently calculated using compressive strength [118 119], as is modulus of elasticity. Empirical regression models based on experimental data are also utilized to determine the shear strength of RC elements [120]. Conventional empirical methods for evaluating the mechanical characteristics of concrete were developed using a predefined equation based on restricted experimental data and parameters. They are only effective for describing their own experimental results, which were used for calibration. If the original data is amended, the model coefficients and equation form must be updated. As a result, standard models may be ineffective for determining mechanical qualities of fresh concrete since the relationship between components and concrete characteristics for particular concrete types is very nonlinear [112-114,121-123]. Furthermore, developing a mathematical model that is widely accepted might be difficult. Another important feature of concrete is dry shrinkage, and its value is critical in determining the ability of concrete buildings to operate over time. Over the last five decades, multiple empirical equations for shrinkage estimation have been developed in various codes, including ACI [124] and CEB [125]. However, it is difficult to obtain correct results using these methods in some circumstances since dry shrinkage is impacted by a variety of parameters related to the concrete composition, specimen size, component quality, and ambient conditions [126].

Designing concrete mixes is the process of finding the proper ingredients and their relative proportions in order to make concrete with the specified strength, workability, and durability at the lowest feasible cost. Conventional concrete mix percentage algorithms are just a generalization of previous experience, which is sometimes available as empirical formulae or tables. Because of the unpredictability of concrete elements (e.g., chemical and mineral admixtures, cement, and fine and coarse aggregates), standard concrete mix proportion algorithms are a trial-and-error exercise that incurs additional expenses and effort [127].

5 Recent progress and future initiatives in durability and service-life evaluation

The degradation of RC structures due by rebar corrosion has been mostly analyzed using carbonation and/or chloride empirical models based on experimental data. Models cannot effectively forecast rebar depassivation time due to complicated factors governing CO2 and Cl− penetration in concrete. Several factors influence the penetration of these aggressive compounds into concrete structures, including material qualities, casting process, workability, curing conditions, and the macro- and microenvironment to which the RC structure is subjected. Furthermore, the rapidly increasing usage of blended supplemental cementitious materials and new technologies render traditional empirical model's incapable of accurately predicting the time to commencement of rebar corrosion [53,144-146]. These limits of empirical models are the causes for the failure to achieve conditions for optimal choice of suitable design, inspection, and maintenance that would ensure a longer service life.

5.1 ***Recent advances***

Prototypes must be capable to account for the majority of the relevant characteristics that regulate degradation mechanisms in sequence to properly anticipate the level of degradation and the structure's balancing "service life". Developing empirical carbonation and/or chloride models that properly address the governing elements is undoubtedly difficult since the actual behavior is a result of various parameters that are difficult to define numerically. As a result, creating a ML-oriented forecast prototypes that can understand from current "long-term in-service" data is a promising option. The remainder of this portion discusses the present direct or indirect uses of ML approaches in supporting the assessment of "carbonation depth and chloride penetration".

The prediction performance was compared to that of NN models, and it was discovered that SVMs have superior accuracy and generalization capabilities. Zhitao et al. [149-151] also used SVM. They used the identical input parameters as those used in Xiang's investigation. The predictive ability of the SVM model was compared to that of the BPNN model. The findings revealed that both models are successful for determining carbonation depth, with SVM outperforming BPNN in terms of prediction capabilities. Other research [152-154] show that machine learning can predict carbonation depth.

Machine learning models can handle practically all governing elements controlling CO2 and Cl− entry into concrete pores, unlike conventional methods [156-164. This allows for the assessment of all controlling aspects as a group rather than individually, ensuring forecast reliability since critical relationships are not overlooked. In another perspective, determining the degree of effect of each parameter that regulates the degradation processes in a typical method is impossible due to the presence of multiple unknown factors. Machine learning can recognize complicated patterns in big datasets, allowing it to reflect intrinsic correlations between parameters [165-173].

5.2 Future directions

As shown in the preceding paragraph, machine learning has clear advantages in analyzing the reliability and "service life of RC structures". Machine learning has long been seen as an important and encouraging tool for managing the ageing of RC structures. Machine learning performance is determined by the amount of data available and the presence of adequate parameters in the data. These data must be collected using monitoring systems[174]. Monitoring systems will be required to collect this data. Depicts the evolution of "monitoring systems" and "machine learning algorithms" for measuring concrete characteristics and structural health. Wired sensors were employed in the 1990s to analyses the functioning of constructions. Wired monitoring systems necessitate the installation and maintenance of expensive communication lines on an ongoing basis. Furthermore, in the long run, constant remote observation utilizing wireless sensors may be more cost-effective than doing periodic field experiments, taking into account labour expenses, user safety, and user fees [176,177]. Smart wireless sensors have lately emerged as a possible separation to present sensor device. It has a solid wireless connection technological device, a separate entity on-board CPU, and a small form factor. Thus, it is unlikely that wireless sensors won't gradually play a significant role in RC structure aging control. Integrated sensors have been employed in several investigations to track concrete parameters [176,178]. Today, there are more than fifty different kinds of sensors that can identify moisture, temperatures, rebar rusting, concrete chemistry, and skeletal modifications [175,179]. To name a few examples, a variety of research have used sensors to monitor rebar corrosion and/or aggressive compounds producing corrosion [180-183]. Comparably, RC structures have made extensive use of sensor-based systems for tracking to analyze atmospheric variables including the climate and humidity levels [175,184-187]. Critical knowledge regarding the degree of decreases, including rebar corrosion, carbonation, freeze-thaw cycles, and alkali-aggregate interaction, may be obtained by keeping an eye on these factors [188]. In general, tracking RC projects allows for a more accurate evaluation of the concrete's effectiveness and also a prompt warning of any problems. Additionally, it would provide important data that may be used to validate current algorithms for service-life prediction, leading to more precise prediction. Additionally, as repair program development and execution may be further optimized, integrating data from surveillance systems in tandem with statistical models for service-life estimation leads in significant reductions in lifetime costs [175–179].The functional life of reinforced concrete buildings was previously predicted using data-driven predictions that employ embedded sensors and previous observational information combined with an inductive model. While strengthening estimation, these methods continue to depend on a theoretical model that has limitations (see Section 2.2). It was inevitable to mix the outcomes of ML algorithms with traditional approaches since there was a lack of data over time from the components that predominantly impact damage activities. In the future, evaluation of RC constructions' reliability and service life will solely be based on information obtained from continuous monitoring using a variety of wireless sensors and algorithms for learning. Large data sets may be effectively mined for insights and used to create models that predict using ML techniques. Furthermore, the use of machine learning methods for SHM, concrete property assessment, and combines design is growing. It suggests that ML is quickly being a popular substitute strategy to ageing RC structures.

RC material evaluation, evaluation, and supervision will need the deployment of wireless sensors and ML approaches to evaluate the material's functionality and service life. By installing sensors in several areas, electronically sharing sensor data, and utilizing machine learning algorithms to analyze it, assessment may be completed swiftly and remotely. None of this could be done on the job location with no the assistance of inspectors. The suggested foreseeable aging management plan for RC structures is shown in Figure 4. The sensors incorporated into the structure will provide information on the time fluctuations and spatial distribution of the elements that drive deterioration, as seen in the organization diagram. The sensor information will be provided to a server for cloud storage. It has a significant benefit in that, with Internet access, varied streams of data may be presented, retrieved, and transferred from any location. The structure's condition may be assessed remotely via explanatory data analysis.

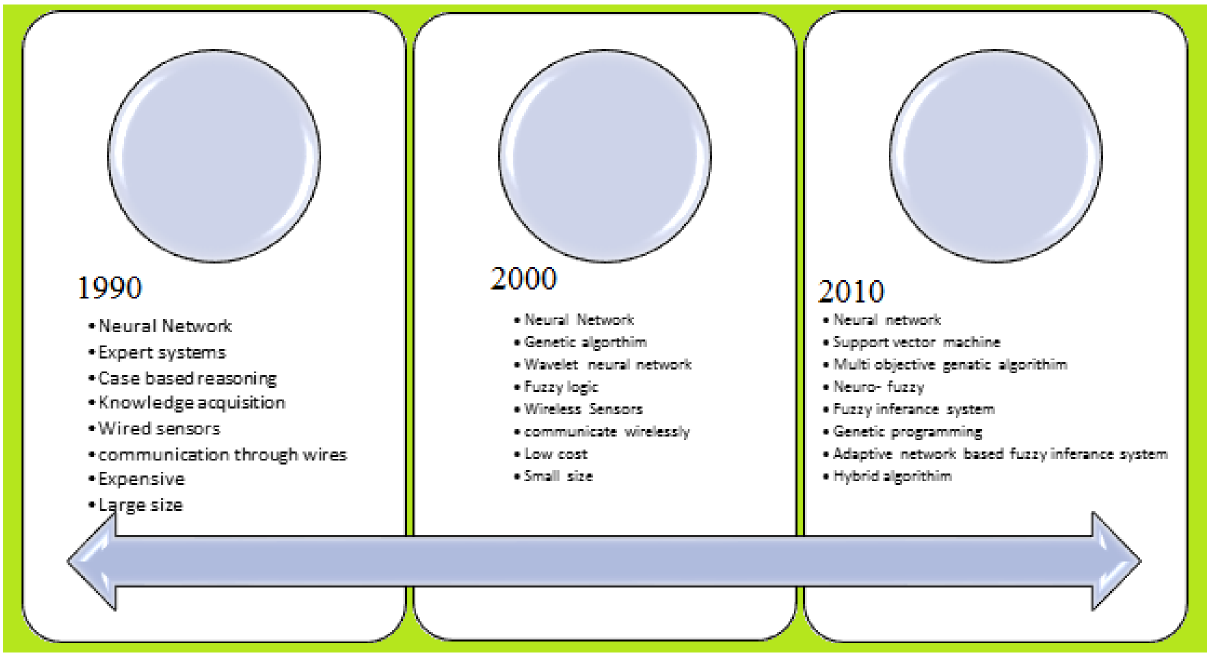

Fig. 3. Sensor and machine learning techniques have advanced in their use in analyzing concrete characteristics and structural health.

Machine learning can understand the complicated interrelationships among parameters collected from sensor data and make predictions without the requirement for an factual model. The forecast authorizes a more real technique for evaluating a structure's service life and precisely scheduling repair actions, significantly lowering maintenance expenditures. As the amount of data available for learning increases, the working of “machine learning-based prototypes” improves adaptively, resulting in more trustworthy predictions. Furthermore, using several sensors allows ML to understand the mixed effect of numerous degradation processes. It also plays an important function in retrieving previously undiscovered information. The acquired knowledge will aid in developing ideal solutions that increase the structure's durability.

6 Conclusions

Current research demonstrated the significance and application of ML for assessing the reliability and “service life of RC structures” by carefully examining its capacity to resolve the shortcomings of frequently used empirical prototypes. Machine learning strategy can understand the intricate interrelationships between major characteristics that influence deterioration mechanisms, allowing them to properly anticipate service life in actual time without the requirement for empirical models. The article also discussed earlier shown applications of ML algorithms for “SHM”, concrete characteristics, and mix formulation. In adding, a latest suggested ML outcome for aiding in the reliability evaluation of “RC structures” is described. Because of the growing usage of wireless sensors for continuous structural observations, ML-based prototypes are anticipated to become the favorable non-destructive and reliable stability assessment approach in the future, bringing about a paradigm change in “service-life prediction”. This strategy aids in the precise planning of repair measures, allowing for significant reductions in prevention and lifetime costs. Further, ML-based prototypes may understand the synergistic effect of many degradation processes utilizing data from numerous sensors, allowing them to uncover hidden insights. The obtained knowledge will help specialists enhanced the concrete mix to provide long-lasting concrete and optimal repair solutions. This study may be expanded by covering all elements of machine learning algorithms in various civil engineering applications.

References-

[1] ACI (American Concrete Institute), Protection of Metals in Concrete Against Corro- sion, ACI 222R-01, 2001.

[2] G.K. Glass, Reinforcement corrosion, in: J. Newman, B.S. Choo (Eds.), Adv. Concr. Technol. 2 Concr. Prop, Elsevier L, Butterworth-Heinemann, Oxford 2003, pp. 8/ 1–9/27.

[3] Z. Wang, Q. Zeng, L. Wang, Y. Yao, K. Li, Corrosion of rebar in concrete under cyclic freeze–thaw and chloride salt action, Constr. Build. Mater. 53 (2014) 40–47, http:// dx.doi.org/10.1016/j.conbuildmat.2013.11.063.

[4] B. Pradhan, Corrosion behavior of steel reinforcement in concrete exposed to com- posite chloride–sulfate environment, Constr. Build. Mater. 72 (2014) 398–410, http://dx.doi.org/10.1016/j.conbuildmat.2014.09.026.

[5] E. Sistonen, Service Life of Hot-dip Galvanised Reinforcement Bars in Carbonated and Chloride-contaminated Concrete, Helsinki University of Technology, 2009 (http://urn.fi/URN:ISBN:978-952-248-168-9).

[6] B. Yu, L. Yang, M. Wu, B. Li, Practical model for predicting corrosion rate of steel re- inforcement in concrete structures, Constr. Build. Mater. 54 (2014) 385–401, http://dx.doi.org/10.1016/j.conbuildmat.2013.12.046.

[7] M. El-Reedy, Steel-reinforced Concrete Structures: Assessment and Repair of Cor- rosion, CRC Press, Boca Raton, FL, 2008http://dx.doi.org/10.1201/9781420054316.

[8] Y. Zhou, B. Gencturk, K. Willam, A. Attar, Carbonation-induced and chloride-in- duced corrosion in reinforced concrete structures, Mater. Civ. Eng. 27 (2015), 04014245. http://dx.doi.org/10.1061/(ASCE)MT.1943-5533.0001209.

[9] G. Markeset, S. Rostam, O. Klinghoffer, Guide for the Use of Stainless Steel Rein- forcement in Concrete Structures, Oslo, 2006.

[10] J.R. Mackechnie, M.G. Alexander, Repair Principles for Corrosion-damaged Rein- forced Concrete Structures, Department of Civil Engineering, University of Cape Town, 2001.

[11] S.L. Matthews, J.R. Morlidge, Performance based rehabilitation of reinforced con- crete structures, in: M.G. Alexander, H.-D. Beushausen, F. Dehn, P. Moyo (Eds.), Concr. Repair, Rehabil. Retrofit. II 2nd Int. Conf. Concr. Repair, Rehabil. Retrofit. ICCRRR-2, CRC Press, Leiden 2008, pp. 277–278, http://dx.doi.org/10.1201/ 9781439828403.ch100.

[12] W.Z. Taffese, E. Sistonen, Service life prediction of repaired structures using con- crete recasting method: state-of-the-art, Procedia Eng. 57 (2013) 1138–1144, http://dx.doi.org/10.1016/j.proeng.2013.04.143.

[13] B. Bissonnette, P.H. Emmons, A.M. Vaysburd, Concrete repair: research and practice
– the critical dimension, in: M.G. Alexander, H.-D. Beushausen, F. Dehn, P. Moyo (Eds.), Concr. Repair, Rehabil. Retrofit. II 2nd Int. Conf. Concr. Repair, Rehabil. Ret- rofit. ICCRRR-2, CRC Press, Leiden 2008, pp. 275–276, http://dx.doi.org/10.1201/ 9781439828403.ch99.

[14] A. Holst, H. Budelmann, H.-J. Wichmann, Improved sensor concepts for durability monitoring of reinforced concrete structures, in: F.-K. Chang (Ed.), Proc. 8th Int. Work. Struct. Heal. Monit. (IWSHM 2011),

DEStech Publications, Inc., Lancaster 2011, pp. 1472–1479.

[15] ACI (American Concrete Institute), Service-life Prediction—State-of-the-art Report, ACI 365.1R-00, 2000 43.

[16] F.H. Wittmann, T. Zhao, F. Jiang, X. Wan, Influence of combined actions on durabil- ity and service life of reinforced concrete structures exposed to aggressive environ- ment, Restor. Build. Monum. 18 (2014) 105–112, http://dx.doi.org/10.1515/rbm-2012-6510.

[17] A. Costa, J. Appleton, Concrete carbonation and chloride penetration in a marine environment, Concr. Sci. Eng. 3 (2001) 242–249.

[18] M.G. Grantham, Understanding defects, testing and inspection, in: M.G. Grantham (Ed.), Concr. Repair a Pract. Guid, CRC Press, Boca Raton, FL 2011, pp. 1–55.

[19] W. McCarter, T. Chrisp, G. Starrs, A. Adamson, E. Owens, P. Basheer, et al., Develop- ments in performance monitoring of concrete exposed to extreme environments, Infrastruct. Syst. 18 (2012) 167–175, http://dx.doi.org/10.1061/(ASCE)IS.1943- 555X.0000089.

[20] W. McCarter, T. Chrisp, G. Starrs, N. Holmes, L. Basheer, M. Basheer, et al., Develop- ments in monitoring techniques for durability assessment of cover-zone concrete, 2nd Int. Conf. Durab. Concr. Struct, Hokkaido University Press, Sapporo 2010, pp. 137–146.

[21] P.K. Wong, Z. Yang, C.M. Vong, J. Zhong, Real-time fault diagnosis for gas turbine generator systems using extreme learning machine, Neurocomputing 128 (2014) 249–257, http://dx.doi.org/10.1016/j.neucom.2013.03.059.

[22] I.E. Mulia, T. Asano, A. Nagayama, Real-time forecasting of near-field tsunami waveforms at coastal areas using a regularized extreme learning machine, Coast. Eng. 109 (2016) 1–8, http://dx.doi.org/10.1016/j.coastaleng.2015.11.010.

[23] L. Bertolini, B. Elsener, P. Pedeferri, R.B. Polde, Corrosion of Steel in Concrete: Pre- vention, Diagnosis, Repair, Wiley-VCH Verlag GmbH & Co. KGaA, Weinheim, 2004http://dx.doi.org/10.1002/3527603379.

[24] A.M. Neville, J.J. Brooks, Concrete Technology, second ed. Prentice Hall, Harlow, 2010.

[25] P.K. Mehta, P.J.M. Monteiro, Concrete: Microstructure, Properties, and Materials, third ed. McGraw-Hill, New York, 2006http://dx.doi.org/10.1036/0071462899.

[26] fib (International Federation for Structural Concrete), Structural Concrete: Text- book on Behaviour, Design and Performance, fib, Lausanne, 2009.

[27] B. Lagerblad, Carbon Dioxide Uptake During Concrete Life Cycle – State of the Art, 2005.

[28] B. Saassouh, Z. Lounis, Probabilistic modeling of chloride-induced corrosion in con- crete structures using first- and second-order reliability methods, Cem. Concr. Compos. 34 (2012) 1082–1093, http://dx.doi.org/10.1016/j.cemconcomp.2012. 05.001.

[29] R. Neves, F.A. Branco, J. De Brito, A method for the use of accelerated carbonation tests in durability design, Constr. Build. Mater. 36 (2012) 585–591, http://dx.doi. org/10.1016/j.conbuildmat.2012.06.028.

[30] A. Köliö, T.A. Pakkala, J. Lahdensivu, M. Kiviste, Durability demands related to car- bonation induced corrosion for Finnish concrete buildings in changing climate, Eng. Struct. 62–63 (2014) 42–52, http://dx.doi.org/10.1016/j.engstruct.2014.01. 032.

[31] C.G. Nogueira, E.D. Leonel, Probabilistic models applied to safety assessment of re- inforced concrete structures subjected to chloride ingress, Eng. Fail. Anal. 31 (2013) 76–89, http://dx.doi.org/10.1016/j.engfailanal.2013.01.023.

[32] J. Zhang, Z. Lounis, Nonlinear relationships between parameters of simplified diffu- sion-based model for service life design of concrete structures exposed to chlo- rides, Cem. Concr. Compos. 31 (2009) 591–600, http://dx.doi.org/10.1016/j. cemconcomp.2009.05.008.

[33] Y. Hosokawa, K. Yamada, B. Johannesson, L.-O. Nilsson, Development of a multi- species mass transport model for concrete with account to thermodynamic phase equilibriums, Mater. Struct. 44 (2011) 1577–1592, http://dx.doi.org/10. 1617/s11527-011-9720-2.

[34] K. Henchi, E. Samson, F. Chapdelaine, J. Marchand, Advanced finite-element predic- tive model for the service life prediction of concrete infrastructures in support of asset management and decision-making, in: L. Soibelman, B. Akinci (Eds.), Proc. 2007 Int. Work. Comput. Civ. Eng, American Society of Civil Engineers, Reston 2007, pp. 870–880, http://dx.doi.org/10.1061/40937(261)103.

[35] E. Bastidas-Arteaga, A. Chateauneuf, M. Sánchez-Silva, P. Bressolette, F. Schoefs, A comprehensive probabilistic model of chloride ingress in unsaturated concrete, Eng. Struct. 33 (2011) 720–730, http://dx.doi.org/10.1016/j.engstruct.2010.11.008.

[36] O.-P. Kari, Long-term Ageing of Concrete Structures in Finnish Rock Caverns as Ap- plication Facilities for Low- and Intermediate-level Nuclear Waste, Aalto Universi- ty, 2015 (http://urn.fi/URN:ISBN:978-952-60-6052-

1).
[37] F. Papworth, A whole of life approach to concrete durability—the CIA concrete du- rability series, in: F. Dehn, H.-D. Beushausen, M.G. Alexander, P. Moyo (Eds.), Concr. Repair, Rehabil. Retrofit. IV Proc. 4th Int. Conf. Concr. Repair, Rehabil. Retrofit, CRC Press, Leiden 2015, pp. 213–219, http://dx.doi.org/10.1201/b18972-30.
[38] K.Y. Ann, S.W. Pack, J.P. Hwang, H.W. Song, S.H. Kim, Service life prediction of a concrete bridge structure subjected to carbonation, Constr. Build. Mater. 24 (2010) 1494–1501, http://dx.doi.org/10.1016/j.conbuildmat.2010.01.023.
[39] O.P. Kari, J. Puttonen, E. Skantz, Reactive transport modelling of long-term carbon- ation, Cem. Concr. Compos. 52 (2014) 42–53, http://dx.doi.org/10.1016/j. cemconcomp.2014.05.003.
[40] C.L. Page, Corrosion and protection of reinforcing steel in concrete, in: C.L. Page,
M.M. Page (Eds.), Durab. Concr. Cem. Compos, Woodhead Publishing Ltd., Cam- bridge, U.K. 2007, pp. 136–186.
[41] H.-W. Song, S.-J. Kwon, Evaluation of chloride penetration in high performance concrete using neural network algorithm and micro pore structure, Cem. Concr. Res. 39 (2009) 814–824, http://dx.doi.org/10.1016/j.cemconres.2009.05.013.
[42] O.P. Kari, J. Puttonen, Simulation of concrete deterioration in Finnish rock cavern conditions for final disposal of nuclear waste, Ann. Nucl. Energy 72 (2014) 20–30, http://dx.doi.org/10.1016/j.anucene.2014.04.035.
[43] P. Schiessl, S. Lay, Influence of concrete composition, in: H. Böhni (Ed.), Corros. Reinf. Concr. Struct, Woodhead Publishing Limited, Cambridge, U.K. 2005, pp. 91–134.
[44] R. Neves, F. Branco, J. De Brito, Field assessment of the relationship between natural and accelerated concrete carbonation resistance, Cem. Concr. Compos. 41 (2013) 9–15, http://dx.doi.org/10.1016/j.cemconcomp.2013.04.006.
[45] fib (International Federation for Structural Concrete), Code-type Models for Con- crete Behaviour: State-of-the-art Report, fib, Lausanne, 2013.
[46] fib (International Federation for Structural Concrete), fib Model Code for Concrete Structures 2010, Ernst & Sohn, Berlin, 2013.
[47] DuraCrete, DuraCrete Final Technical Report: Probabilistic Performance Based Du- rability Design of Concrete Structures, 2000.
[48] L. Tang, L.-O. Nilsson, P.A.M. Basheer, Resistance of Concrete to Chloride Ingress: Testing and Modelling, Boca Raton, FL, 2011, http://dx.doi.org/10.1201/b12603.
[49] J. Marchand, E. Samson, Predicting the service-life of concrete structures – limita- tions of simplified models, Cem. Concr. Compos. 31 (2009) 515–521, http://dx. doi.org/10.1016/j.cemconcomp.2009.01.007.
[50] C. Andrade, R. D'Andrea, N. Rebolledo, Chloride ion penetration in concrete: the re- action factor in the electrical resistivity model, Cem. Concr. Compos. 47 (2014) 41–46, http://dx.doi.org/10.1016/j.cemconcomp.2013.09.022.
[51] G. Morcous, Z. Lounis, Prediction of onset of corrosion in concrete bridge decks using neural networks and case-based reasoning, Comput. Civ. Infrastruct. Eng. 20 (2005) 108–117, http://dx.doi.org/10.1111/j.1467-8667.2005.00380.x.
[52] Y.-M. Sun, T.-P. Chang, M.-T. Liang, Kirchhoff transformation analysis for determin- ing time/depth dependent chloride diffusion coefficient in concrete, J. Mater. Sci. 43 (2008) 1429–1437, http://dx.doi.org/10.1007/s10853-007-2304-4.
[53] J.C. Walraven, Design for service life: how should it be implemented in future codes, in: M.G. Alexander, H.-D. Beushausen, F. Dehn, P. Moyo (Eds.), Concr. Repair, Rehabil. Retrofit. II 2nd Int. Conf. Concr. Repair, Rehabil. Retrofit. ICCRRR-2, CRC Press, Leiden 2008, pp. 3–10, http://dx.doi.org/10.1201/9781439828403.sec1.
[54] R. Bekkerman, M. Bilenko, J. Langford, Scaling up machine learning: introduction, in: R. Bekkerman, M. Bilenko, J. Langford (Eds.), Scaling up Mach. Learn. Parallel Distrib. Approaches, Cambridge University Press, New York 2012, pp. 1–22.
[55] V. Cherkassky, F. Mulier, Learning From Data: Concepts, Theory, and Methods, sec- ond ed. John Wiley & Sons, Inc., Hoboken, NJ, 2007.
[56] J. Han, M. Kamber, J. Pei, Data Mining: Concepts and Techniques, Morgan Kaufmann, Waltham, MA, 2012.
[57] I.H. Witten, E. Frank, M.A. Hall, Data Mining: Practical Machine Learning Tools and Techniques: Practical Machine Learning Tools and Techniques, Morgan Kaufmann, Burlington, MA, 2011.
[58] E. Alpaydin, Introduction to Machine Learning, second ed. MIT Press, Cambridge, MA, 2010http://dx.doi.org/10.1017/S0269888910000056.
[59] Y. Reich, Machine learning techniques for civil engineering problems, Microcomput. Civ. Eng. 12 (1997)

295–310, http://dx.doi.org/10.1111/0885-9507.00065.
[60] V.M. Karbhari, L.S.-W. Lee, Vibration-based damage detection techniques for struc- tural health monitoring of civil infrastructure systems, in: V.M. Karbhari, F. Ansari (Eds.), Struct. Heal. Monit. Civ. Infrastruct. Syst, Woodhead Publishing Limited, Cambridge, U.K. 2009, pp. 177–212.
[61] T. Mitchell, Machine Learning, McGraw Hill, 1997.
[62] M. Kanevski, V. Timonin, A. Pozdnukhov, Machine Learning for Spatial Environ- mental Data: Theory, Applications, and Software, EPFL Press, Lausanne, 2009http://dx.doi.org/10.1201/9781439808085.
[63] S. Marsland, Machine Learning: An Algorithmic Perspective, Chapman and Hall/ CRC, Boca Raton, FL, 2009.
[64] K.P. Murphy, Machine learning: a probabilistic perspective, Machine Learning: A Probabilistic Perspective, Cambridge, MA, 2012.
[65] M. Ivanović, M. Radovanović, Modern machine learning techniques and their ap- plications, in: A. Hussain, M. Ivanović (Eds.), Electron. Commun. Networks IV Proc. 4th Int. Conf. Electron. Commun. Networks, CRC Press, Leiden 2015, pp. 833–846, http://dx.doi.org/10.1201/b18592-153.
[66] T. Harris, Credit scoring using the clustered support vector machine, Expert Syst. Appl. 42 (2015) 741–750, http://dx.doi.org/10.1016/j.eswa.2014.08.029.
[67] A. Takeda, T. Kanamori, Using financial risk measures for analyzing generalization performance of machine learning models, Neural Netw. 57 (2014) 29–38, http:// dx.doi.org/10.1016/j.neunet.2014.05.006.
[68] M.J. Kim, D.K. Kang, Ensemble with neural networks for bankruptcy prediction, Expert Syst. Appl. 37 (2010) 3373–3379, http://dx.doi.org/10.1016/j.eswa.2009.10.012.
[69] K. Di, W. Li, Z. Yue, Y. Sun, Y. Liu, A machine learning approach to crater detection from topographic data, Adv. Space Res. 54 (2014) 2419–2429, http://dx.doi.org/10. 1016/j.asr.2014.08.018.
[70] G. Dede, M.H. Sazlı, Speech recognition with artificial neural networks, Digit. Signal Process. 20 (2010) 763–768, http://dx.doi.org/10.1016/j.dsp.2009.10.004.
[71] W.W. Hsieh, Machine Learning Methods in the Environmental Sciences: Neural Networks and Kernels, Cambridge University Press, Cambridge, 2009http://dx. doi.org/10.1017/CBO9780511627217.
[72] W.Z. Taffese, Case-based reasoning and neural networks for real estate valuation, in: V. Devedžic (Ed.), Proc. 25th IASTED Int. Multi-conference Artif. Intell. Appl, ACTA Press, Anaheim, CA 2007, pp. 84–89.
[73] B. Park, J.K. Bae, Using machine learning algorithms for housing price prediction: the case of Fairfax County, Virginia housing data, Expert Syst. Appl. 42 (2015) 2928–2934, http://dx.doi.org/10.1016/j.eswa.2014.11.040.
[74] W.Z. Taffese, A survey on application of artificial intelligence in real estate industry, in: M.Y. Hamid, A. Chekima, G. Sainarayanan, N. Prabhakaran, P. Anthony, F. Wong, et al., (Eds.), Proc. Third Int. Conf. Artif. Intell. Eng. Technol, Universiti Malaysia Sabah, Kota Kinabalu 2006, pp. 710–715.
[75] K.W. Chau, C.L. Wu, A hybrid model coupled with singular spectrum analysis for daily rainfall prediction, J. Hydroinformatics 12 (2010) 458–473, http://dx.doi. org/10.2166/hydro.2010.032.
[76] R. Taormina, K.-W. Chau, Data-driven input variable selection for rainfall–runoff modeling using binary-coded particle swarm optimization and extreme learning machines, J. Hydrol. 529 (2015) 1617–1632, http://dx.doi.org/10.1016/j.jhydrol. 2015.08.022.
[77] W. Wang, K. Chau, D. Xu, X.-Y. Chen, Improving forecasting accuracy of annual run- off time series using ARIMA based on EEMD decomposition, Water Resour. Manag. 29 (2015) 2655–2675, http://dx.doi.org/10.1007/s11269-015-0962-6.
[78] C.L. Wu, K.W. Chau, Y.S. Li, Methods to improve neural network performance in daily flows prediction, J. Hydrol. 372 (2009) 80–93, http://dx.doi.org/10.1016/j. jhydrol.2009.03.038.
[79] A. Lavecchia, Machine-learning approaches in drug discovery: methods and appli- cations, Drug Discov. Today 20 (2015) 318–331, http://dx.doi.org/10.1016/j.drudis. 2014.10.012.
[80] G. Wang, K.-M. Lam, Z. Deng, K.-S. Choi, Prediction of mortality after radical cystectomy for bladder cancer by machine learning techniques, Comput. Biol. Med. 63 (2015) 124–132, http://dx.doi.org/10.1016/j.compbiomed.2015.05.015.
[81] D. Che, Q. Liu, K. Rasheed, X. Tao, Decision tree and ensemble learning algorithms with their applications in bioinformatics, in: H.R. Arabnia, Q.-N. Tran (Eds.), Softw. Tools Algorithms Biol. Syst, Springer-Verlag, New York 2011, pp. 191–199, http:// dx.doi.org/10.1007/978-1-4419-7046-6.
[82] S. Zhang, K.-W. Chau, Dimension reduction using semi-supervised locally linear embedding for plant leaf classification, in: D.-S. Huang, K.-H. Jo, H.-H. Lee, H.-J. Kang, V. Bevilacqua (Eds.), Emerg. Intell. Comput. Technol. Appl. 5th Int. Conf. Intell. Comput. ICIC 2009, Ulsan, South Korea, Sept. 16-19, 2009. Proc, Springer, Berlin Heidelberg, Heidelberg 2009, pp. 948–955, http://dx.doi.org/10.1007/978- 3-642-04070-2_100.

[83] A. Vaughan, S.V. Bohac, Real-time, adaptive machine learning for non-stationary, near chaotic gasoline engine combustion time series, Neural Netw. 70 (2015) 18–26, http://dx.doi.org/10.1016/j.neunet.2015.04.007.

[84] S. Jurado, À. Nebot, F. Mugica, N. Avellan, Hybrid methodologies for electricity load forecasting: entropy-based feature selection with machine learning and soft com- puting techniques, Energy 86 (2015) 276–291, http://dx.doi.org/10.1016/j.energy. 2015.04.039.

[85] A. Kialashaki, J.R. Reisel, Development and validation of artificial neural network models of the energy demand in the industrial sector of the United States, Energy 76 (2014) 749–760, http://dx.doi.org/10.1016/j.energy.2014.08.072.

[86] T. Arciszewski, M. Mustafa, W. Ziarko, A methodology of design knowledge acqui- sition for use in learning expert systems, Int. J. Man Mach. Stud. 27 (1987) 23–32, http://dx.doi.org/10.1016/S0020-7373(87)80042-1.

[87] J.R. Stone, D.I. Blockley, B.W. Pilsworth, Towards machine learning from case histories, Civ. Eng. Syst. 6 (1989) 129–135, http://dx.doi.org/10.1080/ 02630258908970553.

[88] S. Zheng, Z. Li, H. Wang, A genetic fuzzy radial basis function neural network for structural health monitoring of composite laminated beams, Expert Syst. Appl. 38 (2011) 11837–11842, http://dx.doi.org/10.1016/j.eswa.2011.03.072.

[89] N.L. Khoa, B. Zhang, Y. Wang, F. Chen, S. Mustapha, Robust dimensionality reduction and damage detection approaches in structural health monitoring, Struct. Health Monit. 13 (2014) 406–417, http://dx.doi.org/10.1177/ 1475921714532989.

[90] S.-S. Jin, S. Cho, H.-J. Jung, Adaptive reference updating for vibration-based struc- tural health monitoring under varying environmental conditions, Comput. Struct. 158 (2015) 211–224, http://dx.doi.org/10.1016/j.compstruc.2015.06.001.

[91] S. Yuan, L. Wang, G. Peng, Neural network method based on a new damage signa- ture for structural health monitoring, Thin-Walled Struct. 43 (2005) 553–563, http://dx.doi.org/10.1016/j.tws.2004.10.003.

[92] S. Saadat, M.N. Noori, G.D. Buckner, T. Furukawa, Y. Suzuki, Structural health mon- itoring and damage detection using an intelligent parameter varying (IPV) tech- nique, Int. J. Non Linear Mech. 39 (2004) 1687–1697, http://dx.doi.org/10.1016/j. ijnonlinmec.2004.03.001.

[93] F. Salazar, M.A. Toledo, E. Oñate, R. Morán, An empirical comparison of machine learning techniques for dam behaviour modelling, Struct. Saf. 56 (2015) 9–17, http://dx.doi.org/10.1016/j.strusafe.2015.05.001.

[94] J.-H. Chou, J. Ghaboussi, Genetic algorithm in structural damage detection, Comput. Struct. 79 (2001) 1335–1353, http://dx.doi.org/10.1016/S0045-7949(01)00027-X.

[95] B.A. Story, A Comparative Array of Artificial Neural Networks for Use in Structural Impairment Detection, Texas A&M University, 2012.

[96] M.Q. Feng, D.K. Kim, J.-H. Yi, Y. Chen, Baseline models for bridge performance mon- itoring, J. Eng. Mech. 130 (2004) 562–569, http://dx.doi.org/10.1061/(ASCE)0733- 9399(2004)130:5(562).

[97] Y.-J. Cha, O. Buyukozturk, Modal strain energy based damage detection using multi-objective optimization, in: A. Wicks (Ed.), Struct. Heal. Monit. Vol. 5 Proc. 32nd IMAC, A Conf. Expo. Struct. Dyn. 2014, Springer, Cham 2014, pp. 125–133, http://dx.doi.org/10.1007/978-3-319-04570-2_14.

[98] V. Ranković, N. Grujović, D. Divac, N. Milivojević, A. Novaković, Modelling of dam behaviour based on neuro-fuzzy identification, Eng. Struct. 35 (2012) 107–113, http://dx.doi.org/10.1016/j.engstruct.2011.11.011.

[99] H.Z. Su, Z.P. Wen, Combination model monitoring dam safety with wavelet neural network, in: Z. Wu, M. Abe (Eds.), Proc. First Int. Conf. Struct. Heal. Monit. Intell. Infrastruct, A. A. Balkema, Lisse 2003, pp. 593–600.

[100] H. Hao, Y. Xia, Vibration-based damage detection of structures by genetic algo- rithm, J. Comput. Civ. Eng. 16 (2002) 222–229, http://dx.doi.org/10.1061/ (ASCE)0887-3801(2002)16:3(222).

[101] B. Yan, Y. Cui, L. Zhang, C. Zhang, Y. Yang, Z. Bao, et al., Beam structure damage identification based on BP neural network and support vector machine, Math. Probl. Eng. 2014 (2014) 1–8, http://dx.doi.org/10.1155/2014/850141.

[102] C.-B. Yun, J.-H. Yi, E.Y. Bahng, Joint damage assessment of framed structures using a neural networks technique, Eng. Struct. 23 (2001) 425–435, http://dx.doi.org/10. 1016/S0141-0296(00)00067-5.

[103] J.J. Lee, J.W. Lee, J.H. Yi, C.B. Yun, H.Y. Jung, Neural networks-based damage detec- tion for bridges considering errors in baseline finite element models, J. Sound Vib. 280 (2005) 555–578, http://dx.doi.org/10.1016/j.jsv.2004.01.003.

[104] S.B. Satpal, A. Guha, S. Banerjee, Damage identification in aluminum beams using support vector machine: numerical and experimental studies, Struct. Control. Health Monit. (2015)http://dx.doi.org/10.1002/stc.1773.

[105] S. Soyoz, M.Q. Feng, Long-term monitoring and identification of bridge structural parameters, Comput. Civ. Infrastruct. Eng. 24 (2009) 82–92, http://dx.doi.org/10. 1111/j.1467-8667.2008.00572.x.

[106] I. Karimi, N. Khaji, M.T. Ahmadi, M. Mirzayee, System identification of concrete gravity dams using artificial neural networks based on a hybrid finite element– boundary element approach, Eng. Struct. 32 (2010) 3583–3591, http://dx.doi. org/10.1016/j.engstruct.2010.08.002.

[107] M.P. González, J.L. Zapico, Seismic damage identification in buildings using neural networks and modal data, Comput. Struct. 86 (2008) 416–426, http://dx.doi.org/ 10.1016/j.compstruc.2007.02.021.

[108] J. Mata, Interpretation of concrete dam behaviour with artificial neural network and multiple linear regression models, Eng. Struct. 33 (2011) 903–910, http://dx. doi.org/10.1016/j.engstruct.2010.12.011.

[109] C.-Y. Kao, C.-H. Loh, Monitoring of long-term static deformation data of Fei-Tsui arch dam using artificial neural network-based approaches, Struct. Control. Health Monit. 20 (2013) 282–303, http://dx.doi.org/10.1002/stc.492.

[110] V. Ranković, N. Grujović, D. Divac, N. Milivojević, Development of support vector regression identification model for prediction of dam structural behaviour, Struct. Saf. 48 (2014) 33–39, http://dx.doi.org/10.1016/j.strusafe.2014.02.004.

[111] M.-Y. Cheng, J.-S. Chou, A.F.V. Roy, Y.-W. Wu, High-performance concrete compres- sive strength prediction using time-weighted evolutionary fuzzy support vector machines inference model, Autom. Constr. 28 (2012) 106–115, http://dx.doi.org/ 10.1016/j.autcon.2012.07.004.

[112] U. Atici, Prediction of the strength of mineral admixture concrete using multivari- able regression analysis and an artificial neural network, Expert Syst. Appl. 38 (2011) 9609–9618, http://dx.doi.org/10.1016/j.eswa.2011.01.156.

[113] J.-S. Chou, C.-F. Tsai, A.-D. Pham, Y.-H. Lu, Machine learning in concrete strength simulations: multi-nation data analytics, Constr. Build. Mater. 73 (2014) 771–780, http://dx.doi.org/10.1016/j.conbuildmat.2014.09.054.

[114] I.-C. Yeh, L.-C. Lien, Knowledge discovery of concrete material using Genetic Oper- ation Trees, Expert Syst. Appl. 36 (2009) 5807–5812, http://dx.doi.org/10.1016/j. eswa.2008.07.004.

[115] I. Saini, P. Chandramouli, Prediction of elastic modulus of high strength concrete by Gaussian process regression, Sci. Eng. Res. 4 (2013) 197–198.

[116] A.H. Gandomi, A.H. Alavi, Applications of computational intelligence in behavior simulation of concrete materials, in: X.-S. Yang, S. Koziel (Eds.), Comput. Optim. Appl. Eng. Ind, Springer, Berlin 2011, pp. 221–243, http://dx.doi.org/10.1007/ 978-3-642-20986-4_9.

[117] K. Yan, C. Shi, Prediction of elastic modulus of normal and high strength concrete by support vector machine, Constr. Build. Mater. 24 (2010) 1479–1485, http:// dx.doi.org/10.1016/j.conbuildmat.2010.01.006.

[118] ACI (American Concrete Institute), Building Code Requirements for Structural Con- crete (ACI 318-95) and Commentary (ACI 318R-95), AC1318-95 AC1318R-95, 1995.

[119] CEB (Comité Euro-International du Béton), CEB-FIP Model Code 90, 1993.

[120] M.Y. Mansour, M. Dicleli, J.Y. Lee, J. Zhang, Predicting the shear strength of rein- forced concrete beams using artificial neural networks, Eng. Struct. 26 (2004) 781–799, http://dx.doi.org/10.1016/j.engstruct.2004.01.011.

[121] A. Behnood, K.P. Verian, M.M. Gharehveran, Evaluation of the splitting tensile strength in plain and steel fiber-reinforced concrete based on the compressive strength, Constr. Build. Mater. 98 (2015) 519–529, http://dx.doi.org/10.1016/j. conbuildmat.2015.08.124.

[122] J.-K. Kim, S.H. Han, Y.C. Song, Effect of temperature and aging on the mechanical properties of concrete: part I. Experimental results, Cem. Concr. Res. 32 (2002) 1087–1094, http://dx.doi.org/10.1016/S0008-8846(02)00744-5.

[123] F. Demir, K.A. Korkmaz, Prediction of lower and upper bounds of elastic modulus of high strength concrete, Constr. Build. Mater. 22 (2008) 1385–1393, http://dx.doi. org/10.1016/j.conbuildmat.2007.04.012.

[124] ACI (American Concrete Institute), Guide for Modeling and Calculating Shrinkage and Creep in Hardened Concrete, ACI 209.2R-08, 2008.

[125] Z.P. Bažant, S. Baweja, Creep and shrinkage prediction model for analysis and de- sign of concrete structures: model B3-short form, in: A. Al-Manaseer (Ed.), Adam Nev. Symp. Creep Shrinkage-Structural Des. Eff. ACISP-194, American Con- crete Institute (ACI), Farmington Hills, MI 2000, pp. 85–100.

[126] L. Bal, F. Buyle-Bodin, Artificial neural network for predicting drying shrinkage of concrete, Constr. Build. Mater. 38 (2013) 248–254, http://dx.doi.org/10.1016/j. conbuildmat.2012.08.043.

[127] T. Ji, T. Lin, X. Lin, A concrete mix proportion design algorithm based on artificial neural networks, Cem. Concr. Res. 36 (2006) 1399–1408, http://dx.doi.org/10. 1016/j.cemconres.2006.01.009.

[128] M. Uysal, H. Tanyildizi, Estimation of compressive strength of self compacting con- crete containing

polypropylene fiber and mineral additives exposed to high tem- perature using artificial neural network, Constr. Build. Mater. 27 (2012) 404–414, http://dx.doi.org/10.1016/j.conbuildmat.2011.07.028.

[129] B.K.R. Prasad, H. Eskandari, B.V.V. Reddy, Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN, Constr. Build. Mater. 23 (2009) 117–128, http://dx.doi.org/10.1016/j.conbuildmat.2008.01.014.

[130] R. Siddique, P. Aggarwal, Y. Aggarwal, Prediction of compressive strength of self- compacting concrete containing bottom ash using artificial neural networks, Adv. Eng. Softw. 42 (2011) 780–786, http://dx.doi.org/10.1016/j.advengsoft.2011.05. 016.

[131] A.T.A. Dantas, M.B. Leite, K. de J. Nagahama, Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural net- works, Constr. Build. Mater. 38 (2013) 717–722, http://dx.doi.org/10.1016/j. conbuildmat.2012.09.026.

[132] Z.H. Duan, S.C. Kou, C.S. Poon, Prediction of compressive strength of recycled aggre- gate concrete using artificial neural networks, Constr. Build. Mater. 40 (2013) 1200–1206, http://dx.doi.org/10.1016/j.conbuildmat.2012.04.063.

[133] H. Naderpour, A. Kheyroddin, G.G. Amiri, Prediction of FRP-confined compressive strength of concrete using artificial neural networks, Compos. Struct. 92 (2010) 2817–2829, http://dx.doi.org/10.1016/j.compstruct.2010.04.008.

[134] A. Nazari, J.G. Sanjayan, Modelling of compressive strength of geopolymer paste, mortar and concrete by optimized support vector machine, Ceram. Int. 41 (2015) 12164–12177, http://dx.doi.org/10.1016/j.ceramint.2015.06.037.

[135] A. Nazari, S. Riahi, Prediction split tensile strength and water permeability of high strength concrete containing TiO2 nanoparticles by artificial neural network and genetic programming, Compos. Part B Eng. 42 (2011) 473–488, http://dx.doi.org/ 10.1016/j.compositesb.2010.12.004.

[136] M. Sarıdemir, Empirical modeling of splitting tensile strength from cylinder com- pressive strength of concrete by genetic programming, Expert Syst. Appl. 38 (2011) 14257–14268, http://dx.doi.org/10.1016/j.eswa.2011.04.239.

[137] B. Ahmadi-Nedushan, Prediction of elastic modulus of normal and high strength concrete using ANFIS and optimal nonlinear regression models, Constr. Build. Mater. 36 (2012) 665–673, http://dx.doi.org/10.1016/j.conbuildmat.2012.06.002.

[138] F. Demir, Prediction of elastic modulus of normal and high strength concrete by ar- tificial neural networks, Constr. Build. Mater. 22 (2008) 1428–1435, http://dx.doi. org/10.1016/j.conbuildmat.2007.04.004.

[139] S. Lee, C. Lee, Prediction of shear strength of FRP-reinforced concrete flexural mem- bers without stirrups using artificial neural networks, Eng. Struct. 61 (2014) 99–112, http://dx.doi.org/10.1016/j.engstruct.2014.01.001.

[140] R. Bashir, A. Ashour, Neural network modelling for shear strength of concrete members reinforced with FRP bars, Compos. Part B Eng. 43 (2012) 3198–3207, http://dx.doi.org/10.1016/j.compositesb.2012.04.011.

[141] K. Nasrollahzadeh, M.M. Basiri, Prediction of shear strength of FRP reinforced con- crete beams using fuzzy inference system, Expert Syst. Appl. 41 (2014) 1006–1020, http://dx.doi.org/10.1016/j.eswa.2013.07.045.

[142] K. Mermerdaş, M.M. Arbili, Explicit formulation of drying and autogenous shrink- age of concretes with binary and ternary blends of silica fume and fly ash, Constr. Build. Mater. 94 (2015) 371–379, http://dx.doi.org/10.1016/j.conbuildmat.2015. 07.074.

[143] M.I. Khan, Mix proportions for HPC incorporating multi-cementitious composites using artificial neural networks, Constr. Build. Mater. 28 (2012) 14–20, http://dx. doi.org/10.1016/j.conbuildmat.2011.08.021.

[144] M. Marks, D. Jozwiak-Niedzwiedzka, M.A. Glinicki, Application of machine learning for prediction of concrete resistance to migration of chlorides, in: A.M. Brandt, J. Olek, I.H. Marshall (Eds.), Proc. Int. Symp. “Brittle Matrix Compos. 9”, Woodhead Publishing Ltd. and Institute of Fundamental Technological Research, Warsaw 2009, pp. 227–236.

[145] F. Papworth, A whole of life approach to concrete durability—the CIA concrete du- rability series, in: F. Dehn, H.-D. Beushausen, M.G. Alexander, P. Moyo (Eds.), Concr. Repair, Rehabil. Retrofit. IV 4th Int. Conf. Concr. Repair, Rehabil. Retrofit. ICCRRR-4, CRC Press, Leiden 2015, pp. 213–219, http://dx.doi.org/10.1201/b18972-30.

[146] S.W. Tang, Y. Yao, C. Andrade, Z.J. Li, Recent durability studies on concrete struc- ture, Cem. Concr. Res. 78 (2015) 143–154, http://dx.doi.org/10.1016/j.cemconres. 2015.05.021.

[147] N.R. Buenfeld, N.M. Hassanein, A.J. Jones, An artificial neural network for predicting carbonation depth in concrete structures, in: I. Flood, N. Kartam (Eds.), Artif. Neural Networks Civ. Eng. Adv. Featur. Appl, American Society of Civil Engineers, Reston, VA 1998, pp. 77–117.

[148] C. Lu, R. Liu, Predicting carbonation depth of prestressed concrete under different stress states using artificial neural network, Adv. Artif. Neural Syst. 2009 (2009) 1–8, http://dx.doi.org/10.1155/2009/193139.

[149] W.Z. Taffese, F. Al-Neshawy, E. Sistonen, M. Ferreira, Optimized neural network based carbonation prediction model, Int. Symp. Non-Destructive Test. Civ. Eng. (NDT-CE 2015), Bundesanstalt für Materialforschung und –prüfung (BAM), Berlin 2015, pp. 1074–1083.

[150] R. Xiang, Prediction of concrete carbonation depth based on support vector regres- sion, in: Q. Liu, M. Zhu (Eds.), Third Int. Symp. Intell. Inf. Technol. Appl, IEEE Com- puter Society, Los Alamitos, CA 2009, pp. 172–175, http://dx.doi.org/10.1109/IITA. 2009.469.

[151] L. Zhitao, H. Hongming, Z. Shengli, Research on support vector machine's predic- tion of concrete carbonization, in: Q. Luo (Ed.), Int. Semin. Bus. Inf. Manag, IEEE Computer Society, Los Alamitos, CA 2008, pp. 319–322, http://dx.doi.org/10. 1109/ISBIM.2008.206.

[152] N. Bu, G. Yang, H. Zhao, Prediction of concrete carbonization depth based on DE-BP neural network, in: Q. Luo, M. Zhu (Eds.), Third Int. Symp. Intell. Inf. Technol. Appl. IITA 2009, IEEE Computer Society, Los Alamitos, CA 2009, pp. 240–243, http://dx. doi.org/10.1109/IITA.2009.252.

[153] D. Luo, D. Niu, Z. Dong, Application of neural network for concrete carbonation depth prediction, in: J. Olek, J. Weiss (Eds.), Proc. 4th Int. Conf. Durab. Concr. Struct, Purdue University Press, West Lafayette, IN 2014, pp. 66–71, http://dx.doi.org/10. 5703/1288284315384.

[154] Y. Liu, S. Zhao, C. Yi, The forecast of carbonation depth of concrete based on RBF neural network, in: Q. Zhou, J. Luo (Eds.), Second Int. Symp. Intell. Inf. Technol. Appl. IITA 2008, IEEE Computer Society, Los Alamitos, CA 2008, pp. 544–548, http://dx.doi.org/10.1109/IITA.2008.402.

[155] W.Z. Taffese, E. Sistonen, J. Puttonen, Prediction of concrete carbonation depth using decision trees, in: M. Verleysen (Ed.), Proc. 23rd Eur. Symp. Artif. Neural Networks, Comput. Intell. Mach. Learn, ESANN 2015, pp. 415–420.

[156] W.Z. Taffese, E. Sistonen, J. Puttonen, CaPrM: carbonation prediction model for re- inforced concrete using machine learning methods, Constr. Build. Mater. 100 (2015) 70–82, http://dx.doi.org/10.1016/j.conbuildmat.2015.09.058.

[157] J. Peng, Z. Li, B. Ma, Neural network analysis of chloride diffusion in concrete, J. Mater. Civ. Eng. 14 (2002) 327–333, http://dx.doi.org/10.1061/(ASCE)0899- 1561(2002)14:4(327).

[158] S. Inthata, W. Kowtanapanich, R. Cheerarot, Prediction of chloride permeability of concretes containing ground pozzolans by artificial neural networks, Mater. Struct. 46 (2013) 1707–1721, http://dx.doi.org/10.1617/s11527-012-0009-x.

[159] S.S. Gilan, H.B. Jovein, A.A. Ramezanianpour, Hybrid support vector regression – particle swarm optimization for prediction of compressive strength and RCPT of concretes containing metakaolin, Constr. Build. Mater. 34 (2012) 321–329, http://dx.doi.org/10.1016/j.conbuildmat.2012.02.038.

[160] N. Ghafoori, M. Najimi, J. Sobhani, M.A. Aqel, Predicting rapid chloride permeability of self-consolidating concrete: a comparative study on statistical and neural net- work models, Constr. Build. Mater. 44 (2013) 381–390, http://dx.doi.org/10. 1016/j.conbuildmat.2013.03.039.

[161] A.R. Boğa, M. Öztürk, İ.B. Topçu, Using ANN and ANFIS to predict the mechanical and chloride permeability properties of concrete containing GGBFS and CNI, Compos. Part B Eng. 45 (2013) 688–696, http://dx.doi.org/10.1016/j.compositesb. 2012.05.054.

[162] H. Yasarer, Y.M. Najjar, Characterizing the permeability of Kansas concrete mixes used in PCC pavements, Int. J. Geomech. 14 (2014), 04014017. http://dx.doi.org/ 10.1061/(ASCE)GM.1943-5622.0000362.

[163] Y.-Y. Kim, B.-J. Lee, S.-J. Kwon, Evaluation technique of chloride penetration using apparent diffusion coefficient and neural network algorithm, Adv. Mater. Sci. Eng. (2014)http://dx.doi.org/10.1155/2014/647243 (Article ID, 13 pages).

[164] J. Lizarazo-Marriaga, P. Claisse, Determination of the concrete chloride diffusion co- efficient based on an electrochemical test and an optimization model, Mater. Chem. Phys. 117 (2009) 536–543, http://dx.doi.org/10.1016/j.matchemphys. 2009.06.047.

[165] O.A. Hodhod, H.I. Ahmed, Developing an artificial neural network model to evalu- ate chloride diffusivity in high performance concrete, HBRC J. 9 (2013) 15–21, http://dx.doi.org/10.1016/j.hbrcj.2013.04.001.

[166] A. Tarighat, A.H. Erfanimanesh, Artificial neural network modeling of chloride dif- fusion coefficient and electrical resistivity for ordinary and high performance semi- lightweight concretes, 34th Our World Concr. Struct, CI-Premier Pte Ltd., 2009

[167] A. Delnavaz, A.A. Ramezanianpour, H.R. Ashrafi, The analysis of chloride diffusion coefficient in concrete based on neural network models, in: A.A. Tasnimi (Ed.), Third Int. Conf. Concr. Dev, Building and Housing Research Center, Tehran 2009, pp. 775–782.

[168] W. Mazer, M. Geimba de Lima, Numerical model based on fuzzy logic for predicting penetration of chloride ions into the reinforced concrete structures - first esti- mates, in: V.P. de Freitas, H. Corvacho, M. Lacasse (Eds.), XII DBMC 12th Int. Conf. Durab. Build. Mater. Compon, FEUP Edições, Porto, 2011.

[169] H.-C. Cho, H. Ju, J.-Y. Oh, K.J. Lee, K.W. Hahm, K.S. Kim, Estimation of concrete car- bonation depth considering multiple influencing factors on the deterioration of du- rability for reinforced concrete structures, Adv. Mater. Sci. Eng. 2016 (2016) 1–18, http://dx.doi.org/10.1155/2016/4814609.

[170] A. Delnavaz, A.A. Ramezanianpour, The assessment of carbonation effect on chlo- ride diffusion in concrete based on artificial neural network model, Mag. Concr. Res. 64 (2012) 877–884, http://dx.doi.org/10.1680/macr.11.00059.

[171] M. Marks, M.A. Glinicki, K. Gibas, Prediction of the chloride resistance of concrete modified with high calcium fly ash using machine learning, Materials (Basel) 8 (2015) 8714–8727, http://dx.doi.org/10.3390/ma8125483.

[172] M. Marks, D. Jozwiak-Niedzwiedzka, M.A. Glinicki, Automatic categorization of chloride migration into concrete modified with CFBC ash, Comput. Concr. 9 (2012) 375–387, http://dx.doi.org/10.12989/cac.2012.9.5.375.

[173] R. Parichatprecha, P. Nimityongskul, Analysis of durability of high performance concrete using artificial neural networks, Constr. Build. Mater. 23 (2009) 910–917, http://dx.doi.org/10.1016/j.conbuildmat.2008.04.015.

[174] B. Aygün, V.C. Gungor, Wireless sensor networks for structure health monitoring: recent advances and future research directions, Sens. Rev. 31 (2011) 261–276, http://dx.doi.org/10.1108/02602281111140038.

[175] N. Barroca, L.M. Borges, F.J. Velez, F. Monteiro, M. Górski, J. Castro-Gomes, Wireless sensor networks for temperature and humidity monitoring within concrete struc- tures, Constr. Build. Mater. 40 (2013) 1156–1166, http://dx.doi.org/10.1016/j. conbuildmat.2012.11.087.

[176] W.J. McCarter, Ø. Vennesland, Sensor systems for use in reinforced concrete struc- tures, Constr. Build. Mater. 18 (2004) 351–358, http://dx.doi.org/10.1016/j. conbuildmat.2004.03.008.

[177] D. Cusson, Z. Lounis, L. Daigle, Durability monitoring for improved service life pre- dictions of concrete bridge decks in corrosive environments, Comput. Civ. Infrastruct. Eng. 26 (2011) 524–541, http://dx.doi.org/10.1111/j.1467-8667.2010. 00710.x.

[178] W. McCarter, T. Chrisp, A. Butler, P.A. Basheer, Near–surface sensors for condition monitoring of cover-zone concrete, Constr. Build. Mater. 15 (2001) 115–124, http://dx.doi.org/10.1016/S0950-0618(00)00060-X.

[179] K. Kumar, S. Muralidharan, T. Manjula, M.S. Karthikeyan, N. Palaniswamy, Sensor systems for corrosion monitoring in concrete structures, Sens. Trans. Mag. 67 (2006) 553–560.

[180] J.M. Gandía-Romero, R. Bataller, P. Monzón, I. Campos, E. García-Breijo, M. Valcuende, et al., Characterization of embeddable potentiometric thick-film sen- sors for monitoring chloride penetration in concrete, Sensors Actuators B Chem. 222 (2016) 407–418, http://dx.doi.org/10.1016/j.snb.2015.07.056.

[181] S.P. Karthick, S. Muralidharan, V. Saraswathy, K. Thangavel, Long-term relative per- formance of embedded sensor and surface mounted electrode for corrosion mon- itoring of steel in concrete structures, Sensors Actuators B Chem. 192 (2014) 303–309, http://dx.doi.org/10.1016/j.snb.2013.10.123.

[182] A. Brenna, L. Lazzari, M. Ormellese, Monitoring chloride-induced corrosion of car- bon steel tendons in concrete using a multi-electrode system, Constr. Build. Mater. 96 (2015) 434–441, http://dx.doi.org/10.1016/j.conbuildmat.2015.08.037.

[183] G. Qiao, G. Sun, Y. Hong, Y. Qiu, J. Ou, Remote corrosion monitoring of the RC struc- tures using the electrochemical wireless energy-harvesting sensors and networks, NDT E Int. 44 (2011) 583–588, http://dx.doi.org/10.1016/j.ndteint.2011.06.007.

[184] W.Z. Taffese, E. Sistonen, Neural network based hygrothermal prediction for dete- rioration risk analysis of surface-protected concrete façade element, Constr. Build. Mater. 113 (2016) 34–48, http://dx.doi.org/10.1016/j.conbuildmat.2016.03.029.

[185] F. Al-Neshawy, J. Piironen, S. Peltola, E. Sistonen, J. Puttonen, Network system for assessing the moisture and thermal behaviour of repaired concrete building fa- cades, Inf. Technol. Constr. 16 (2011) 601–616.

[186] A. Norris, M. Saafi, P. Romine, Temperature and moisture monitoring in concrete structures using embedded nanotechnology/microelectromechanical systems (MEMS) sensors, Constr. Build. Mater. 22 (2008) 111–120, http://dx.doi.org/10. 1016/j.conbuildmat.2006.05.047.

[187] W.Z. Taffese, F. Al-Neshawy, J. Piironen, E. Sistonen, J. Puttonen, Monitoring, evalu- ation and long-term forecasting of hygrothermal performance of thick-walled con- crete structure, Proc. OECD/NEA WGIAGE Work. Non-Destructive Eval. Thick. Concr. Struct, OECD, Prague 2014, pp. 121–143.

[188] M. Raupach, J. Gulikers, K. Reichling, Condition survey with embedded sensors re- garding reinforcement corrosion, Mater. Corros. 64 (2012) 141–146, http://dx.doi. org/10.1002/maco.201206629.